INTRODUCTION

The primary goal of this research project is to understand the predictability of the terrestrial hydrologic cycle at seasonal time scales and to develop methodologies that facilitate the development and testing operational seasonal hydrologic forecasts over the Eastern U.S.

FIRST-YEAR RESEARCH ACTIVITIES AND RESULTS

The major research activities in the first year of the project can be summarized as the following:
1) Develop the methodology for producing seasonal hydrologic forecasting
2) Construct a VIC-base seasonal hydrologic ensemble forecast system
3) Identify regions to carry out the experimental forecasting
4) Make experimental forecasts and hindcasts over the selected regions, and evaluate the performance of the system
5) Monitor the U.S. drought in realtime

As shown previously by Wood et al. (2002), it is possible to force the hydrological model with seasonal meteorological forecast from GCMs such as the NCEP global spectral model (GSM). In that study, they illustrated their methodology, and focused on how to correct the seasonal forecast model bias and how to downscale the GCM forecasts to scales that are appropriate for hydrologic applications. However, that method has critical limitations. Their forecast method implicitly assumes that GCM forecasts are skillful, since the GCM forecasts are directly transferred into the observed distribution without any consideration of their skill and usefulness. Because the skill of seasonal streamflow forecast is significantly affected by the skill of the meteorological forcing, in particular, precipitation and temperature, such an assumption will significantly limits the skill of seasonal hydrologic forecasts. This is because GCMs are not very skillful in predicting seasonal precipitation and temperature over the mid-latitudes. The second limitation is that their methods can only produces the same number of ensembles as provided by the GCM, which for hydrologic applications may be insufficient.

Although the seasonal climate model forecasts are not very skillful, they still provide useful information. Thus what is needed is a better method to extract more fully the useful information from the climate model forecasts. During the last year we developed a Bayesian approach for merging multiple seasonal climate model forecasts to produce a more reliable and skillful seasonal forecast, following on and expanding the work of super-ensemble forecasts. In our Bayesian framework, the climatological distribution is selected as the prior distribution, which reflects our best estimate of the possible outcome, both in its mean and variability, in the absence of any seasonal climate model forecast. The climate model forecasts are used to update the prior distribution through a likelihood function. Each climate model is evaluated by comparing its hindcasts against observations; hence a proper weight can be assigned to each model based on its past performance (i.e. skill). A likelihood function is built based the current forecast and past forecast performance. From this and the prior distribution, a posterior probability distribution is calculated and used to estimate monthly precipitation (and temperature) and its uncertainty. In principle, climate models that are lack precipitation (temperature) forecast skill will contribute less to the posterior distribution. Therefore, such an approach is expected to extract useful information from each model/data sources that will result in our best estimate. This approach was initially tested with sea surface temperature (SST) seasonal forecast from ECMWF DEMETER project, in which each of the seven climate models produce a 9-member ensemble forecast with lead time up to 6 months. Figure 1 illustrates how the posterior (multi-model posterior) is better than the climatology and the original model forecasts. The merged forecast shows the smallest root mean square (RMS) error in comparison to the climatological forecast and the original model forecasts (see Figure 2).

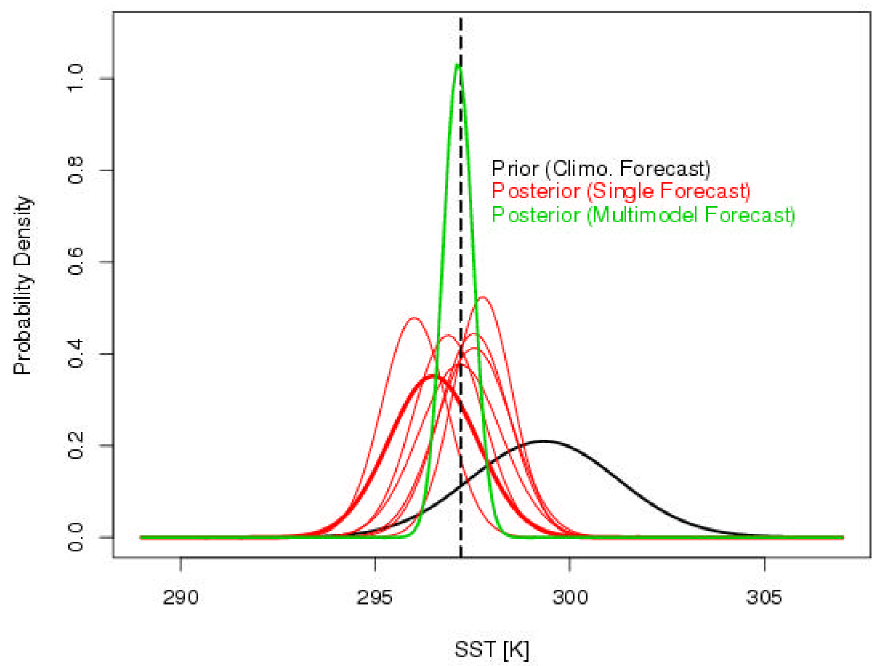

Figure 1: The prior distribution (solid black), single model posterior forecasts (red) and the multi-model posterior forecast (green) for a forecast of SST of 1 grid box over the Nino 3.4 region. The ECMWF DEMETER forecasts are used here. The vertical dashed line indicates the actual observation for that forecast.

A VIC-based seasonal hydrological ensemble forecast system has been developed. The system consists of four building blocks as illustrated by Figure 3. The Bayesian merging approach is one of the central elements in processing the atmospheric ensemble forcing. In our system, the ensemble forecast from NCEP Climate Forecast System (CFS) are merged with observed climatology to produce a posterior distribution of monthly precipitation and air temperature at a $1/8^{th}$-degree spatial scale during the forecast period. The merging effectively takes care of bias correction and spatial downscaling at the same time as when the likelihood function is computed. The downscaled atmospheric forcing is then used to drive the VIC model to produce ensemble forecasts of soil moisture and streamflow. Using the computed posterior distribution, allows us to generate as many ensembles as desired for forcing the VIC hydrologic model.

The forecast has been implemented over the Southeastern U.S., and we now routinely produce seasonal forecasts with lead-times up to 9 months. In the retrospective mode, the forecast system

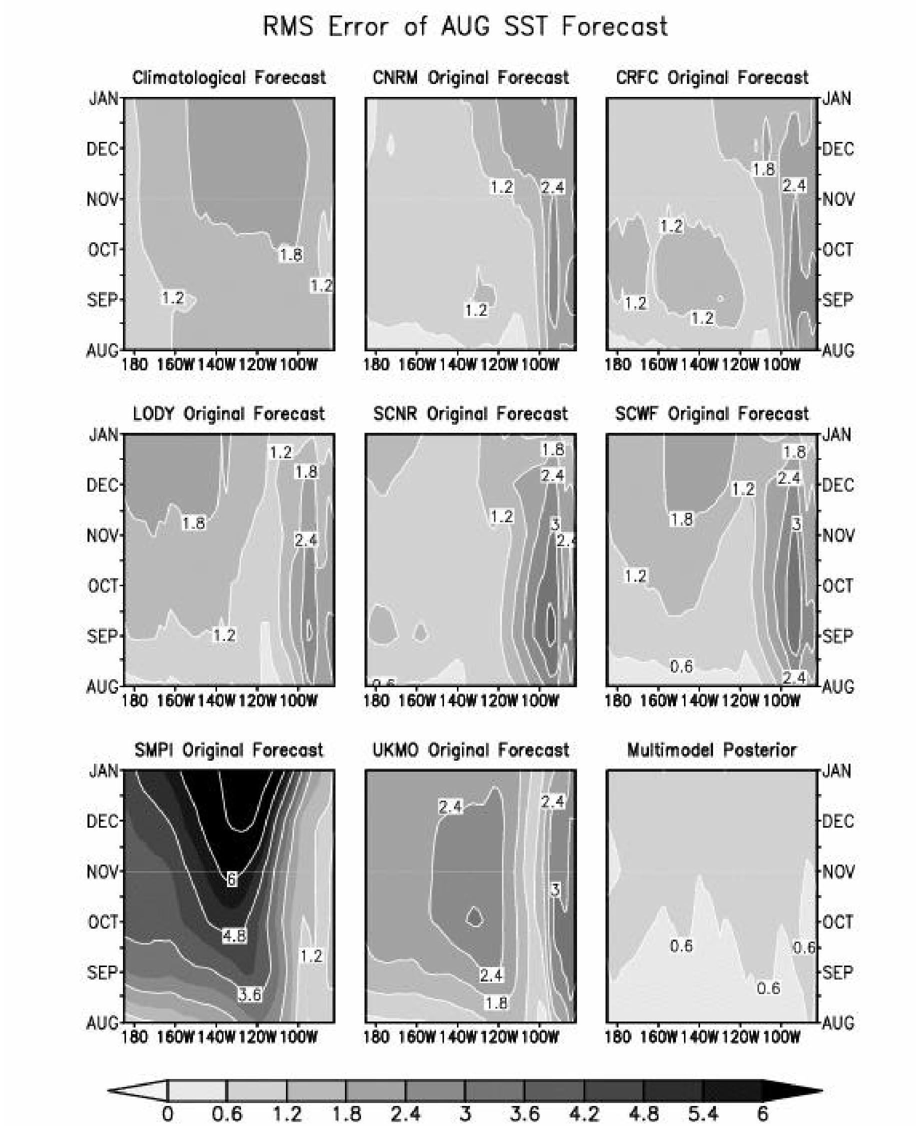

Figure 2: The variation of RMS error with lead time and location from difference forecasts: climatological forecast, original forecast from seven DEMETER climate models, and the posterior forecast using the seven model forecast and the climatological forecast. This is for all the forecasts starting from August.

takes seasonal forecast from CFS and seven ECMWF DEMETER climate models and produces a multi-model posterior forecast before driving the VIC hydrological model. The retrospective period covers the last 20 years and will be used to evaluate the performance of the forecast system. Figure 4 shows an example of the downscaled precipitation forcing from the posterior forecast and compared with observations. The CFS-based forecast and multi-model forecast resemble the anomaly patterns of the observed precipitation, which is shown at the 3-month lead-time. Figure 5 shows the streamflow forecast from one selected USGS gage. The shaded background area is the climatological distribution of the monthly streamflow at this gauge. The actual realization is plotted as black. The system shows some skill over at the 3-month lead-time.

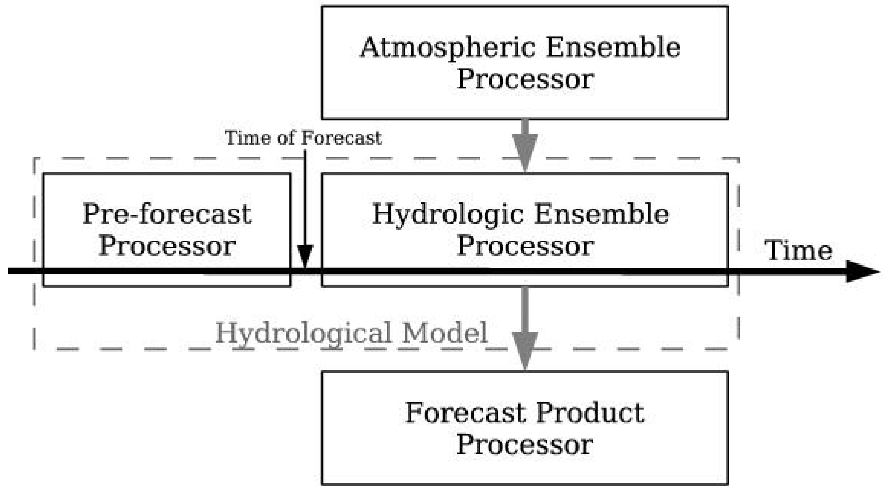

Figure 3: The seasonal hydrologic ensemble forecast system consists of four basic elements. The hydrological model (VIC) is used in both the pre-forecast processor and hydrologic ensemble processor. The Bayesian merging is implemented in the atmospheric ensemble processor.

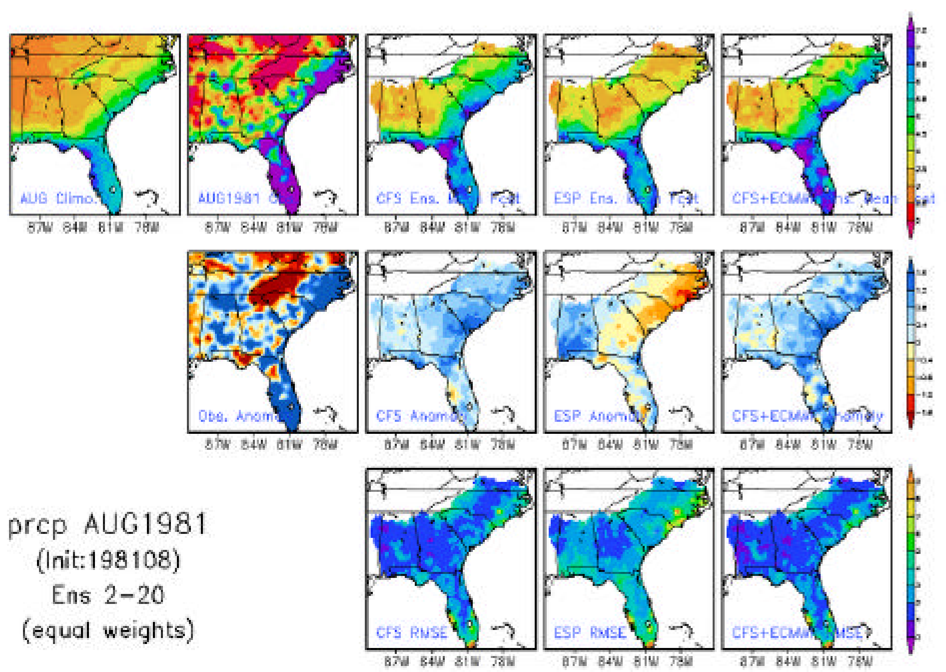

Figure 4: Precipitation forecast for the Southeastern U.S. targeted for Aug. 1981 initialized at May 1981. The second row shows the anomalies with respect to the same observed climatology. The third row is the root mean square (RMS) error of the ensemble with respect to the actual realization.

In conjunction with the hydrologic forecasting, we also developed a real-time (nowcasting) drought monitoring system over the US. using VIC model and North American Land Data Assimilation (NLDAS) products. Our system produces a real-time drought map based on continuous hydrologic modeling. The drought anomalies are similar to the official NOAA drought monitor but avoid the qualitative assessment used in that product, and has greater spatial detail (see figure 6). We have set up a web site (http://hydrology.princeton.edu/forecast) for this project where the latest forecasts and drought nowcasts can be accessed.

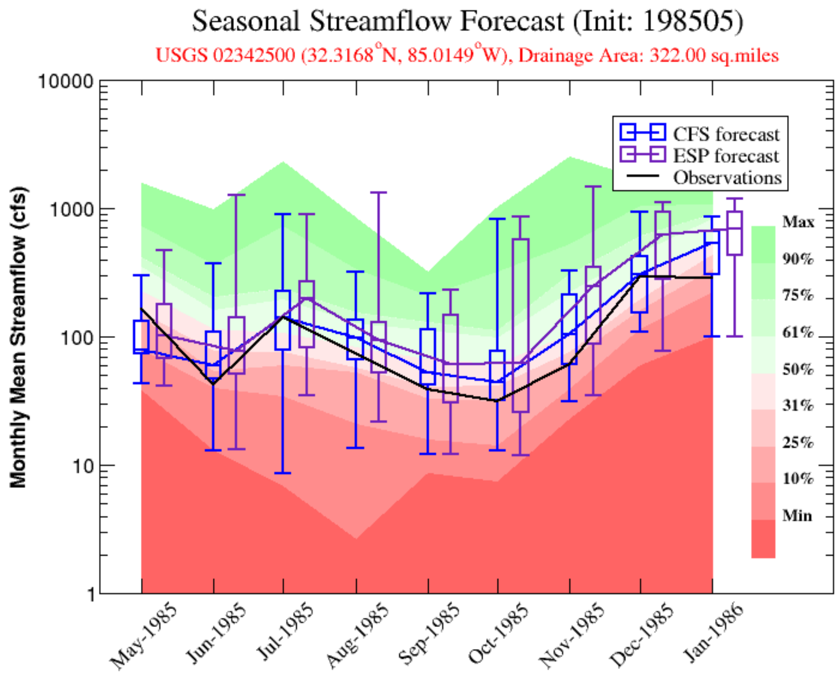

Figure 5: Streamflow forecast for one selected USGS gage.

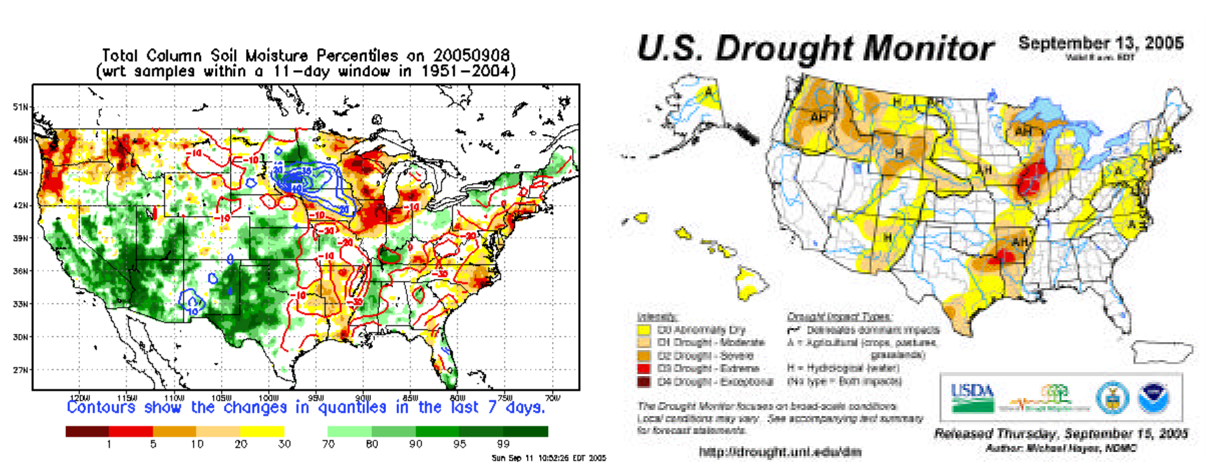

Figure 6: Real-time drought monitoring using VIC and NLDAS compared with official NOAA drought monitor.